Step and curb detection for autonomous vehicles with an algebraic derivative-based approach applied on laser rangefinder data

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***Abstract*— Personal Mobility Vehicles (PMV) is is an important part of the Intelligent Transportation System (ITS) domain. These new transport systems have been designed for urban traffic areas, pedestrian streets, green zones and private parks. In these areas, steps and curbs make the movement of disable or mobility reduced people with PMV, and with standard chair wheels difficult. In this paper, we present a step and curb detection system based on laser sensors. This system is dedicated to vehicles able to cross over steps, for transportation systems, as well as for mobile robots. The system is based on the study of the first derivative of the altitude and highlights the use of a new algebraic derivative method adapted to laser sensor data. The system has been tested on several real scenarios. It provides the distance, altitude and orientation of the steps in front of the vehicle and offers a high level of precision, even with small steps and challenging scenarios such as stairs.**

I. INTRODUCTION

The mobility of elderly and disabled people is a matter of great importance for the research in Intelligent Transportation Systems (ITS). Nevertheless, some urban environments, such as buildings or train stations, are not equipped with elevators and ramps. Moreover, many street corners has sidewalks, which make their access difficult with standard chair wheels, creating hazardous situations. For these reasons, new Personal Mobility Vehicles (PMV) has been recently designed to improve mobility and safety in different areas.

Several manufactures and researchers are focusing on the developments of new PMV systems. The i-unit and i-real project (Toyota), the Segway Human Transporter (Segway Inc.), the Electric Networked Vehicle (EN-V) (General Motor) and TopChair[1] illustrate the great importance of these systems in the market. Like in any other ITS system, the perception of the environment is a critical part of the PMV architecture. In this paper, we focus on the perception of any kind of steps, stairs and curbs.

A lot of work have been done with multilayer laser sensors for the terrain navigation and obstacle detection. In [1], the authors propose a pedestrian detection considering a stochastic recursive Bayesian framework. They used the Sampling Importance-Resampling-based Particle Filter (SIR PF), achieving a good observation of pedestrian movement. Besides, the fusion information, considering laser and stereo vision data, has been tested in [2] with real vehicles in urban scenarios. This approach also uses Bayesian fusion techniques. Other works try to recognize structured areas in indoor and outdoor scenarios [3], using a mobile robot with 3D scanning and plane geometry.

In [4], an algorithm based on stereo-vision for the estimation of the geometric planes in a 3D scenario with different steps and stairs is presented and showed good performances for the curb and step detection. The step detection is also important for blind people. For this target, a virtual white cane for dynamic environment exploration using active triangulation is designed in [5].

From the robotic point of view, there are some applications for step detection. A fully autonomous stair climbing robot is presented in [6], [7]. This system provide information about the size of the steps of a staircase and the position of the staircase in the global area, in order to control the robot with fuzzy techniques, by using computer vision techniques. Other autonomous climbing application can be found with humanoids. In [8], information coming from a laser and a camera are merged to detect steps and both devices are installed in the head of the robot. Although these systems are not PMVs, scenarios, we have to deal with, are similar.

With respect to these previous works, a new perception system for stair detection was designed and an altitude derivative-based approach for step/curb detection was developed. The system is composed on three laser sensors. Two laser sensors are scanning vertically to the ground to provide information of the environment altitude. The third sensor is classically scanning horizontally to the ground in order to detect other obstacles. The other contribution of this paper is an original distance-based approach for algebraic derivative calculation based on [9] and adapted to laser sensor constraint. This work has been developed in the framework of the Personal Intelligent City Accessible Vehicle (PICAV) project. The PICAV is a new PMV for passengers ensuring accessibility for everyone in urban pedestrian environments[2]. This work describes the perception system developed for step and curb detection. The same configuration of the sensors has been installed on a Cybercar at INRIA [10], to test our algorithms in a real platform and environment.

This paper is organized as follows. The system is described in Sec. II. In Sec. III, the theoretical contribution for derivative calculation is presented. The step detection algorithm is explained in Sec. IV and tested in real scenarios in Sec. V. Finally, the conclusions are drawn in Sec. VI.

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[2]http://www.dimec.unige.it/pmar/picav/

II. STEP DETECTION SYSTEM

A. System description

The stair detection system is composed of three laser range finders. Hokuyo UTM 30 LX devices were chosen for their large detection angle (270°) and their high angular resolution (0.25°) and range (30m). Two Hokuyo are mounted in the front of the vehicle, in each extremity of a metal bar within a 70 cm distance. They are adjusted with a given orientation described in Fig. 1-a in protective metal boxes. A third Hokuyo is mounted in the middle of the metal bar and is dedicated to the insurmountable obstacle detection (such as walls or pedestrian). This information can be integrated as part of the obstacle detection algorithms, which are out of this paper scope.

The system is dedicated to the Picav vehicle [11] (Fig. 1-c), which is supposed to be able to cross over a stair, but was first mounted on our Cycab experimental platform (Fig. 1-b) for preliminary tests.

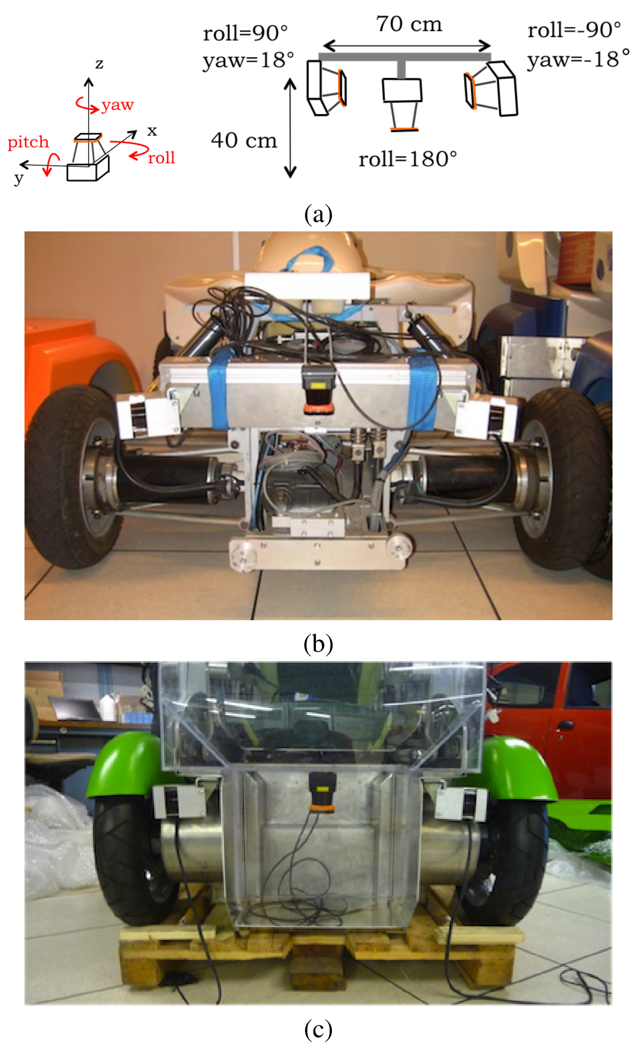
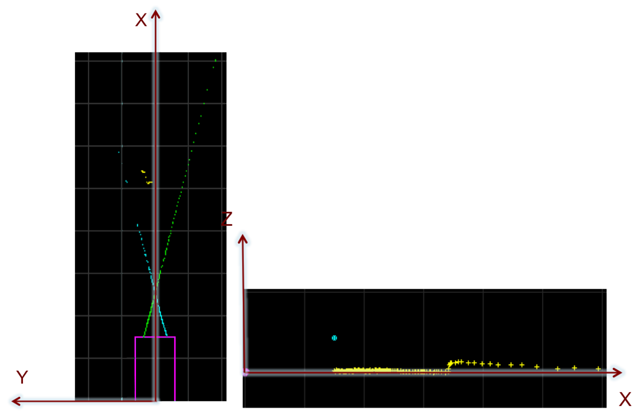


Fig. 1. Step and curb detection system

B. Problem positioning

The two laser sensors dedicated to the step detection have a vertical orientation in order to scan the altitude profile of the environment over two lines of sight shown in cyan and green in Fig. 2-a. The two lines of sight cross each other at 1 m. With this sensor configuration, step and stairs clearly appear just by regarding the altitude Z-axis (see Fig. 2-b, where a step clearly appears at 4.3 m). The middle laser sensor is placed with a zero yaw and pitch angle in order to have a line of sight perpendicular to the ground.



(a) (b)

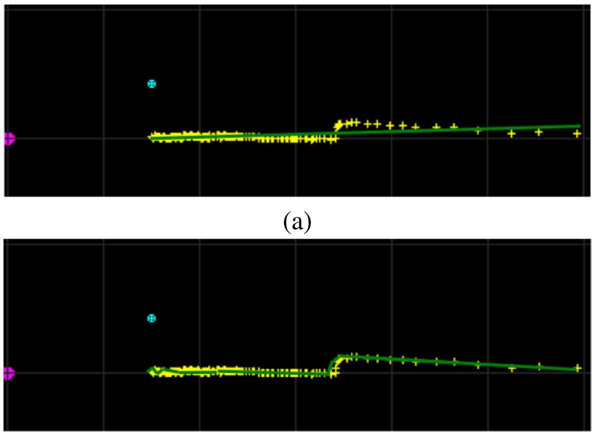
Fig. 2. (a) Bird eye view of laser measurements *-Magenta rectangle represents the ego-vehicle and cyan, green and yellow points represent respectively laser impacts coming from the right, left and middle laser sensors* - (b) Altitude profile of laser data coming from one sensor scanning one stair at 4.3 m *Blue circle represent the sensor position and yellow crosses are the laser impacts*

The main issue is to detect steps considering XZ points profile as shown in Fig. 2-b in a robust and timely manner.

C. Segmentation algorithm

A basic approach would be to use a recursive line fitting algorithm as it is classically employed for obstacle detection [12], [13]. However, this algorithm requires the use of a threshold σ_r, which would be critical for the step detection. The distance σ_r represents the maximum accepted distance between a laser impact and the segment it belongs to. If σ_r is too big, then steps are not detected, because only one segment is detected. In Fig. 3-a, with $\sigma_r = 0.15$ m, the 12 cm step is not detected. If it is too small (here $\sigma_r = 0.05$), several segments can be detected (specially for points close to the sensor where data is noisy), and the step assessment becomes ambiguous. Moreover, a second parameter would be required on the minimum orientation (angle to the ground) of the segment to belong to a step, which means that weak slope stairs could not be detected.

Therefore, an original approach based on the study of the first derivative of the altitude is developed in this work. A description of the algebraic derivative-based distance method is presented in the next section.



(a)

(b)

Fig. 3. Segmentation results (a) with a big σ_r - (b) with a small σ_r *Green lines represent segmentation result*

III. ALGEBRAIC DERIVATIVE-BASED DISTANCE METHOD

A. Existing approach

In [14], an algebraic approach for numerical derivation for signal processing is proposed. This is classically used for parametric estimation [15] and fault diagnosis and fault tolerant control in noisy environment [9] since many years. More recently, this approach is used for marginal applications such as the curvature extrema detection [16].

Considering a temporal signal $x(t)$, the signal can be locally approximated at $t = t_0$ as:

$$x_N(t) = \sum_{i=0}^{N} x^{(i)}(t_0)\frac{t^i}{i!} \quad (1)$$

by considering the truncated Taylor expansion at order N.

Calculation of the derivative coefficients can then be made by using the Laplace transform [16].

In our altitude derivative calculation application, the problem can be translated in the following manner. Each laser scanner impact i is written as: $P_i = [x_i, y_i, z_i]$ in a $xyz-$coordinate system. In order to process a bijective function, altitude is considered as a signal depending on d, the traveled distance over scanning angle. It can be locally represented as a first order polynomial function, $\forall(a_o, a_1) \in \mathbb{R}^2$:

$$z_i(d) = a_0 + a_1 \cdot d \quad (2)$$

Estimate $\hat{a}_1$ is then equivalent to calculate the first order derivative of the altitude z_i. By successive calculus operations (for more calculation details see [16]), eq. (2) can be expressed in the Laplace domain as:

$$-\frac{a_1}{s^4} = \frac{Z_i(s)}{s^2} + \frac{1}{s}\frac{dZ_i(s)}{ds} \quad (3)$$

where $Z_i(s)$ is the operational expression of $z_i(x)$. Using classical operational to time domain transformation rules and Cauchy formula, estimation of the first derivative of the altitude can be limited to one integral:

$$\hat{a}_1 = -\frac{3!}{D^3}\int_0^D (D - 2\delta)z_i(\delta)d\delta \quad (4)$$

where D is the length of the integration window.

What is now specific to our application is directly linked to our laser scanner data. Indeed, D cannot be simply chosen as the temporal length of a fixed number of samples due to the concentration of impact in a closed area to the sensor. Moreover, data are not sorted according to their temporal arrival, but according to their scanning angle as shown in Fig. 4 where a stair can be seen at 4 m and a wall at 10 m.

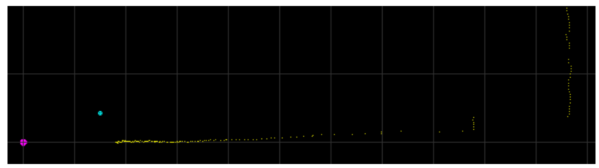


Fig. 4. Laser impact constraint illustration *Magenta cross is the origin of the system coordinates - Cyan cross is the position of the sensor - Yellow points are the laser impacts*

That is the reason why, our implementation must be adapted to the following constraints:

- variable density of points
- no temporal constraints: sorted points according to their scanning angle
- variable intensity for noise process

B. Derivative-based distance approach

Considering all these constraints, the dependence of z to a distance in eq.(2) is justified.

The first derivative of the altitude is thus calculated by using a trapezoidal rule of integration.

$$\hat{a}_1(i) = \frac{3!}{D^3}\sum_{j=0}^{N} d(j-1,j)\left(D - 2\cdot\sum_{k=0}^{j} d(k-1,k)\right)z_j(d) \quad (5)$$

This is similar to eq. (6) in [17], but by considering a non constant sampling period and thus different sliding windows lengths D are considered. Two issues must thus be solved. The first is how to calculate the distance and the second is how to choose the sliding windows length considering the variable point density.

1) Distance calculation: Two options are here described, for which results will be compared in Sec. V:

- Using the Cartesian distance between two successive points. However, it looks dangerous with noisy data (in the area close to the sensor for example). Indeed, with the trapezoidal integration, distance between two points can be seen a a weight dedicated to one sample. Noisy points would be more strongly weighted than non-noisy points. That is why a second option is considered.

- Using a recursive line fitting algorithm. Each sample is then attached to an oriented segment. If the corresponding segment orientation to the ground is higher than $\pi/4$ then, the segment is Y-oriented and the distance between two samples is calculated as the Y-difference. Otherwise, the X-axis is considered.

2) Sliding windows length: As the sampling density is variable, a constant number of samples cannot be used to calculate the first derivative of the altitude. Indeed, the density is very high for points which are closed to the sensor, then density decreases with distance except if the orientation of the reflecting surface is not flat as illustrated on the top figure of Fig. 5. In this scenario a 20 cm stair is seen at 5 m by the system as well as a wall at 9 m. Instead of using a constant number of samples, the number of samples which covers a given accumulated distance D_{max} is considered. In Fig. 5, $D_{max} = 15$ cm is used. This value must be adapted by regarding the application and the sensor resolution (noise).

Results of the first derivative of the altitude processing are shown in the middle and bottom figures of Fig. 5 to illustrate the difference observed between the two distance calculation methods. Both results are quite similar, but the Euclidean distance method provide less noisy results and peaks are higher, meaning that peaks are easier to detect. Another advantage is that it is less computationally expensive, because no preliminary step are required. Only Euclidean distance calculation will be thus considered in the rest of the paper.

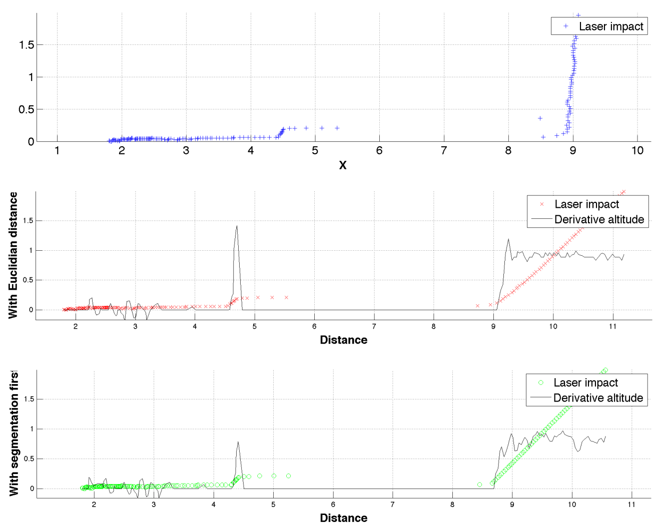


Fig. 5. First derivative of the altitude calculation with the two distance calculation methods

IV. STAIR DETECTION ALGORITHM

A. General overview

General scheme of the stair detection process is proposed in Fig. 6. Original data are first projected on Z-axis. Only XZ-coordinated are considered to calculate the first derivative of the altitude (see Sec. III). An algorithm is then implemented to detect peaks in the first derivative of the altitude curve (see Sec. IV-B). Finally, data coming from the two laser sensors are merged in order to provide, in a robust manner, an estimation of the stair (position, height and orientation) as described in Sec. IV-C.

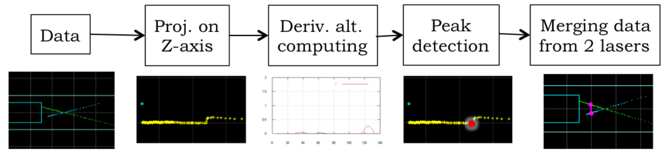


Fig. 6. Block diagram

B. Peak detection

Peak detection in a noisy environment is a well known problem in signal processing. In our step detection application, peaks correspond to changes in the orientation of the ground. A peak maximum corresponds to the top of the step and beginning of the peak to the base of the step. With these information, the system can assess the situation and decide to pass over the step or not.

The second derivative of the altitude $\ddot{z}_i$ is first calculated as the difference between two successive first derivative values. Then, derivative values are scanned since it is higher than a derivative value threshold denoted Th. In this case, a change in the orientation of the ground is detected. The algorithm goes back to previous points to detect the beginning of the peak, corresponding to the base of the step, as described in the pseudo algorithm IV.1. Then the maximum value of the peak and its end are searched until $\ddot{z}_i > \epsilon$ and $ddotz_i < \epsilon$. In order to avoid multi-detection, it must satisfy the following condition: the first derivative of the altitude difference between the peak value and the end of the peak value must be lower than the Th threshold. As an output, peaks are described as a set of N_p peaks characterized by their start, maximum and end indexes.

It is well understanding that the condition in line 3 is necessary to detect ascending stairs. The same algorithm can be applied to detect negative peak and descending steps just by applying the respective condition ($\dot{z}_i < 0$ & $\ddot{z}_i < 0$) and adapting the detection of rising and failing edges for descending stairs.

Algorithm IV.1 Peak detection

0: **Input :** $\{\dot{z}_i, \ddot{z}_i\}, \forall i < N_s$: 1st and 2nd deriv. alt.
1: **for** $i := 0$ **to** N_s **do**
2:   **if** $|\dot{z}_i| > Th$ **then**
3:     **if** $\dot{z}_i > 0$ & $\ddot{z}_i > 0$ **then**
4:       $i := i - 1$
5:       **while** $i <$ previous i_{end}& $\ddot{z}_i > \epsilon$ **do**
6:         $i := i - 1$
7:       **end while**
8:       $i_{start} := i$
9:       **while** $\ddot{z}_i > -\epsilon$ **do**
10:         $i_{max} := i$
11:         $i := i + 1$
12:       **end while**
13:       **while** $\ddot{z}_i < \epsilon$ **do**

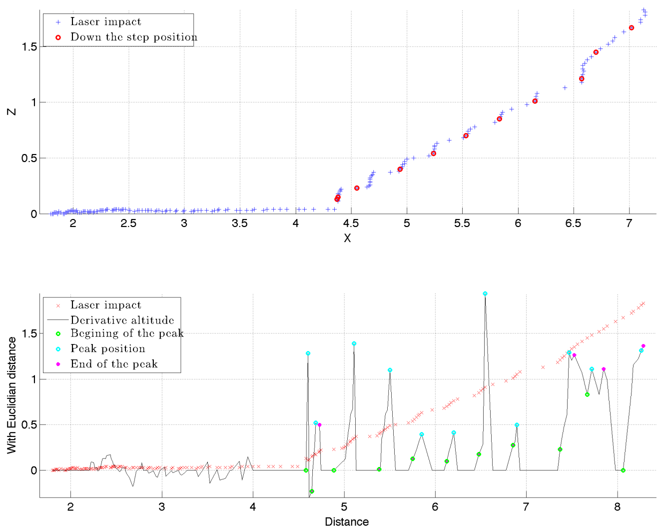


Fig. 7. Peak detection with a challenging staircase

$i := i + 1$
end while
while $\dot{z}_{i_{max}} - \dot{z}_i < Th$ **do**
$i := i + 1$
end while
$i_{end} := i$
save peak
end if
end if
end for

Output : $\{i^n_{star}, i^n_{max}, i^n_{end}\}, \forall n < N_p$: Peak descriptione

In Fig. 7, results of the peak detection algorithm are shown on a challenging staircase scenario. The staircase has seven steps and is surrounded by trees and bushes. The seven steps are perfectly detected at 3 m distance to the sensor. The higher the steps, the fewer points there are, but even in these conditions, the step detection algorithm is effective.

C. Merging information coming from the two sensors

The last stage consists in merging the information coming from the two lasers sensors. This stage can become very challenging in case of staircase for example. Steps detected by the left and right laser sensor are associated to each others. Association feasibility is calculated by considering two parameters:

- the X location
- the step height

When left and right steps are associated, the location, height and orientation of the step is sent to the vehicle which decides to cross over the step or not.

V. EXPERIMENTAL RESULTS

Step detection system, embedded on a Cybercar vehicle, was tested on several real scenarios. Considering the yaw of the two sensors and their corresponding line of sight as well

Fig. 8. (a) 18 cm stair scenario - (b) 12 cm scenario - (c) Descending and ascending stair - (d) Staircase

as an area of interest of one meter at each side of the vehicle, the system should be able to detect stairs until 6 m ahead.

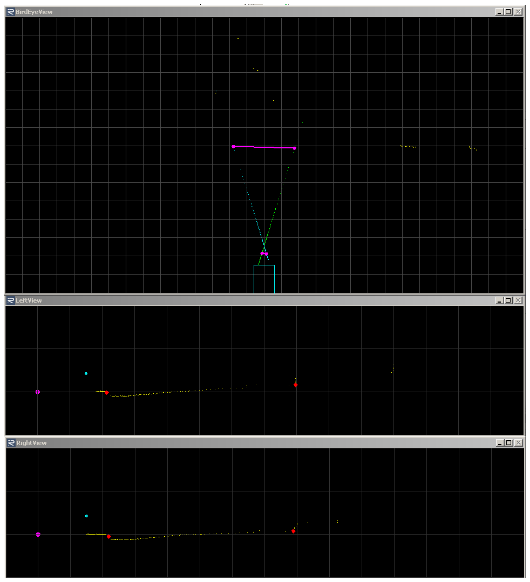
Results are shown for four scenarios of increasing difficulty, illustrated in Fig 8. Parameters are set as follows: $Th = 0.3$ and $\epsilon = 0.01$.

The first scenario is a classical 18 cm curb detection (see Fig. 8-a). The step is perpendicular to the ground and a wall is located at 2 m in the left. The vehicle is slowly moving starting perpendicularly and at 12 m to the curb. The stair is first seen by the sensors and detected at 8 m by the stair detection system and continuously since 4.5 m.

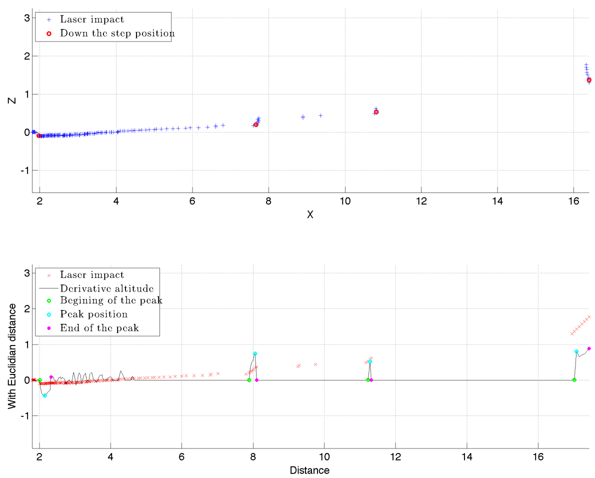
The second scenario (see Fig. 8-b) is quite similar for the vehicle trajectory, but the step is only 12 cm and forms an angle of 45° with the ground. Due to the small height and the shape of the stair, it is harder to detect it and it is first detected at 4.5 m and then continuously detected since 3 m.

The third scenario is even more challenging. The Cybercar is placed on the sidewalk at 2 m to the end of the sidewalk and perpendicularly to the road, meaning that the sidewalk at the other side of the road can also be seen by the system. Curbs are both 18 cm height. The descending step is detected at the beginning of the experiment and the ascending one at 6.5 m distance as illustrated in Fig. 9.

The fourth scenario deals with a seven-step staircase. In this case, both detection and merging are challenging. Detection of steps at the top of the stairs is more difficult because few laser impacts describe them and are located on the front part of the step, not on the top part. However, results shown in [18] prove that the system is still effective



(a)



(b)

Fig. 9. Descending step scenario (a) Bird eye view and altitude profile - (b) Peak detection

in such scenarios, because since the stairs are seen by the sensors, they are detected and correctly evaluated, leading to an effective merging to provide reliable information about the position, size and orientation of the stairs.

VI. CONCLUSION

A new system dedicated to stair detection for PMVs was presented in this paper. An original approach based on the study of the fist derivative of the altitude was proposed and a contribution for the derivative calculation was first tested. First experimental results are promising and the system should be now tested on the PICAV for the end of the project, in order to create original control strategies to cross over stairs.

Further developments could be also imagined for the step detection system itself. To improve result consistency, tracking system should highly improve detection continuity. Detection could also be extended to slope detection, by detecting plate on the derivative curve. Finally, this method could be adapted with stereo-vision sensors for navigable space detection.

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